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Review

Maximizing the Integration of a Battery Energy Storage System–Photovoltaic Distributed Generation for Power System Harmonic Reduction: An Overview

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Abstract: The highly variable power generated from a battery energy storage system (BESS)–photovoltaic distributed generation (PVDG) causes harmonic distortions in distribution systems (DSs) due to the intermittent nature of solar energy and high voltage rises or falls in the BESS. Harmonic distortions are major concerns in the DS, especially when the sizes and locations of these resources are sub-optimal. As a result, many studies are being performed on the optimal allocation of BESS/PVDG systems in distribution network systems. In this regard, this paper seeks to review the existing planning models, optimization methods and renewable energy resources that uncertainty models have employed in solving BESS/PVDGs allocation problems in terms of obtaining optimal solutions/allocations and curtailing the harmonic contents of the DSs. However, studies on optimal allocation planning of BESS/PVDGs have achieved minimum cost but were not able to meet the standard harmonic level of the DSs. The results identified GA, PSO and AIS as some of the most used methodologies while LP, MILP and different configurations of NLP were used in the model formulations of BESS/PVDGs problems. The results also revealed DC-link voltage and switching and grid voltage harmonics as the notable causes and sources of harmonic distortions in BESS/PVDG systems. The current allocation models presented in the recent literature for the planning of BESS/PVDGs do not include the variables necessary for curtailing the harmonic contents in their planning formulations. This paper, therefore, recommends an improved and all-encompassing planning model with an efficient intelligent search algorithm capable of obtaining a global optimum solution and curtailing harmonic distortions from the BESS/PVDG-connected DSs.

Keywords: photovoltaic distributed generation; battery energy storage system; distribution network system; optimization methodologies; harmonic distortions

1. Introduction

The rapid expansion in socioeconomics has led to increasing global energy demand and usage. To balance the resulting widening energy deficiency, renewable energy distributed generation (REDG) is considered as an effective approach to solve the rising energy demand and other power system issues that are technical, economic and environmental in nature [1–3]. REDGs are generation technologies integrated at distribution networks near load users to satisfy immediate power demand, defer network upgrade, enhance power quality and reliability, diversify energy resources, and to reduce power losses, distribution and transmission loading, distribution and transmission costs and on-peak operating costs [4].

The battery energy storage system–photovoltaic DG (BESS/PVDG) is a viable renewable option because the resources are inexhaustible, complementary, economically profitable, environmentally friendly and bi-directional [5–8]. However, the power generated from BESS/PVDG depends on charge and discharge schedules of BESS, which is associated with high voltage rise or fall, and temperature and irradiation of solar energy that is intermittent in nature [6,9–11]. Hence, a substantial number of research studies have unanimously agreed/concurred that harmonics occur in the distribution system when BESS/PVDG units are absorbed due to the intermittent and variable nature of PVDG output power and the high variability of voltage and frequency of BESS schedules. In essence, current harmonics occur as a result of sudden disparity between the aggregate output power of BESS/PVDGs and other generations and the total power demand at an instant in a distribution system. The high rises and falls of the voltage and frequency from battery charge/discharge schedules may result in voltage harmonics [11].

The harmonic distortions are a troubling power quality issue for BESS/PVDG power generation, and they have significant consequences on the DNs. The extent of current harmonics is determined by the active output power from BESS/PVDGs. Thus, the magnitudes of current harmonics are enormous at utility-scale BESS/PVDGs penetration levels. The intermittency of PVDG units and the high voltage rise or fall from BESS/PVDG raise concerns on distribution system harmonic distortions, which have negative effects on power quality, stability and reliability of distribution systems [6,12,13]. The high harmonic contents in the power system lead to increased losses in system elements such as transformers and generating plants; economic costs such as productivity, energy and device/equipment losses; and fire hazards due to overheating of system elements [7,14,15]. The issues mentioned make the integration of a large-scale BESS/PVDG into the distribution systems difficult [6,15,16]. Meanwhile, the locations and sizes of BESS/PVDG units could either improve or impair the magnitudes current and voltage harmonic levels of the networks [17–19]. The mentioned issues make the solution of BESS/PVDG allocation problems formulated using simple mathematical models unrealistic. A realistic model, therefore, requires a dynamic model representation of the network, the use of multi-period planning horizon as well as all the necessary constraints. The problem then becomes a multi-objective one with a maximisation of renewable active and reactive powers into the DNs and a minimisation of the total cost subject to the capacity, investment, technical, stability and harmonic constraints throughout the planning horizon.

Several studies have been performed to proffer optimal solutions for the planning allocation of BESS/PVDG in distribution systems [11,13,16,20–23]. The studies on optimal planning of REDG allocation warrant detailed investigations on the prospects of BESS/PVDGs for generating power, the impact on the DNs, and the effects on the inadequate availability and rising cost of energy, the global economy and environment. Various researchers have reviewed some aspects of the BESS/PVDG allocation planning (BESS/PVDGs-AP) problem. Many solution algorithms, planning models, and emerging technologies deployed in BESS/PVDG-AP have been presented [24–28]. Zahraee et al. [24] presented an analysis of some artificial intelligence optimum plans used in the optimization and sizing of hybrid renewable energy systems. The main contribution of this work is the extensive penetration of renewable energy features for economic performance of the systems. The authors in [25] dealt with the review of some solutions that were used to improve the ability of the distribution system to cope with variable renewable energy source unpredictability such as energy storage technologies, PV and wind energy systems. This study concluded that battery energy storage and pump hydro energy storage are the most used technologies to improve the impact of the variable renewable power on distribution systems. A review presented by Hannan et al. [26] on the planning of BESS and renewable energy hybrid DGs discussed the optimal sizing objectives, various optimization models, the BESS system constraints together with their advantages and weaknesses. A detailed discussion of the BESS applications and shortage of optimal BESS sizing models could be identified as the strong point of this study. In [27], a review of the latest research developments and challenges on optimal planning of a BESS-PVDG connected distribution system was presented. The authors suggested key parameters in the process of optimal planning for a PV–battery system such as economic and technical data, objective functions, energy management schemes, design constraints, optimization algorithms, and electricity pricing regimes.

In view of the contribution of the existing review works on the BESS/PVDGs-AP problem, this study is distinct in these ways:

- Based on the authors' awareness, no literature has presented the evaluation of harmonic components of BESS/PVDGs during integration into distribution networks/systems.
- Unlike the existing reviews, this review presents an overview of harmonic distortions in battery energy storage–photovoltaic hybrid distributed generation systems.
- This study provides a methodology for curtailing harmonic distortions from the BESS/PVDGs-connected distribution systems.
- Moreover, a substantial and diverse number of optimization/solution algorithms deployed in solving the BESS/PVDGs allocation problem is surveyed, comparing all their characteristics to assist the researchers to utilize them successfully and in a cost-effective way.

Despite numerous reviews and studies on BESS/PVDGs, some aspects have not been adequately captured for investigation, review and research. These themes, bulleted above, are comprehensively treated in this paper.

The remaining parts of this paper are organized as follows: Section 2 presents the overview of harmonic components in the BESS/PVDG connected distribution networks. Section 3 details a review of various optimization models and techniques published in the existing research works and some promising algorithms that are recently introduced and used for solving BESS/PVDG allocation optimization problems. The methodological approach for curtailing the harmonic distortions in a BESS/PVDG connected distribution system is presented in Section 4. The characteristics of all the models and techniques are compared, and their shortcomings are discussed under Results and Discussion in Section 5, to assist the researchers in choosing and applying them successfully and in a cost-effective way. Section 6 is the concluding part of the paper, and the recommendations for future research directions are also presented here.

2. Overview of Harmonic Components in BESS/PVDG Systems

Power system harmonic distortion is a major issue for power utilities throughout the world. In recent times, statistical analysis reports have revealed that power system harmonics has become a very troubling power quality issue in BESS/PVDG systems. These harmonics have resonating impacts in generating other power quality problems in large-scale BESS/PVDG [7,15,29–31]. The sources of harmonics produced in BESS/PVDGs are broadly classified into DC-link voltage harmonics, switching harmonics and grid voltage harmonics [7,32].

2.1. DC-Link Voltage Harmonics

The DC-link voltage ripples have become a major source of harmonics produced by BESS/PVDGs [32]. The DC-link voltage harmonics are generated by PVDGs due to solar irradiation intermittency and the high rises or falls of BESS voltage. Du et al. [32] illustrated this phenomenon with the experimental setup simulated in MATLAB Simulink. The experimental results in Figure 1 show that the harmonic distortion increases as DC-link voltage increases. However, these harmonics are usually taken as constant in the analyses and designs of BESS/PVDG inverters. They are not always so in the practical sense. This accounts for the odd harmonic frequencies discovered in the spectrum of BESS/PVDG inverter's output current [33]. In addition, Mansor et al. [34] investigated harmonic generation in three-phase BESS/PVDG inverters and found that the second-order harmonics in the DC link produced the third-order harmonic discovered on the AC side of the inverter. [34]. Many methods have been proposed by the researchers to eliminate the current harmonics generated by the DC-link voltage ripple [35–39]. Some of the proposed methods reduced the dynamic performance of the system, and many lack quality information on the connection between the output current harmonics and DC-link voltage ripples [32].

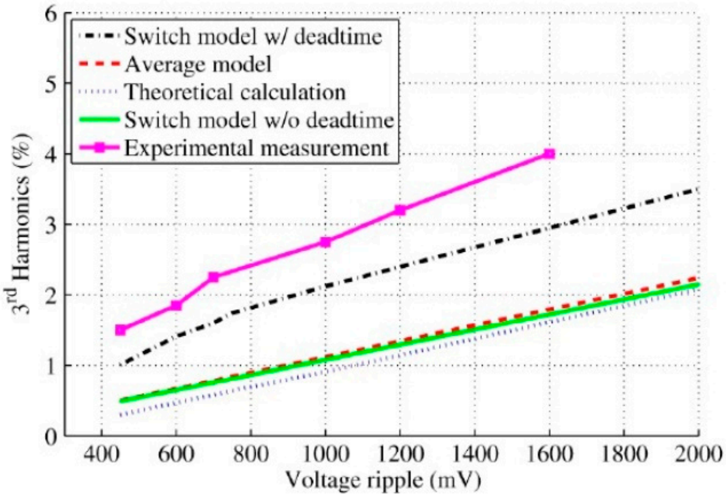


Figure 1. Impact of BESS/PVDG DC-link voltage ripples on harmonics [32].

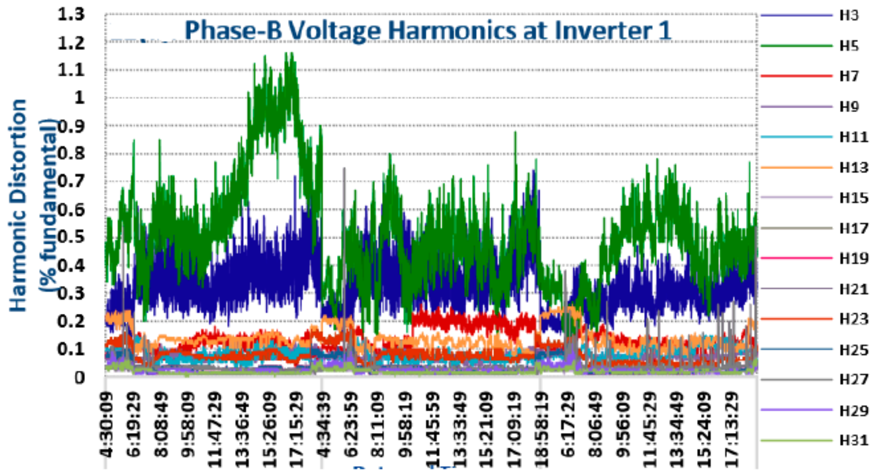
2.2. Switching Harmonics

Switching harmonics is one other cause of current harmonics in BESS/PVDG inverter output. It occurs due to a mismatch in thee generation of switching pulses. The switching harmonics in PWM inverters always double their switching frequency [40,41]. Switching harmonics are very difficult to control and require an appropriate control strategy and optimized BESS/PVDG units; otherwise, system instabilities, harmonic generation and power losses ensue [32,42,43]. Various researchers have presented different methods to control or eliminate the switching harmonics of BESS/PVDG inverters [40,44,45].

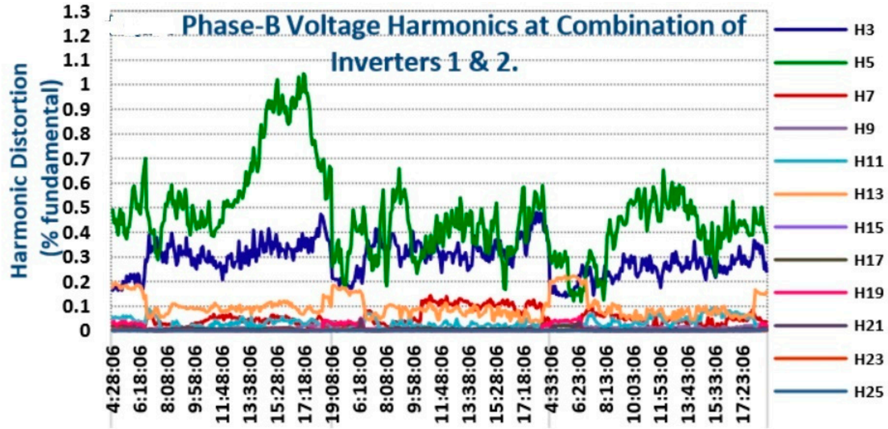
Other research works maintained that the effects of quantization and resolution on control systems' measuring instruments are another potent source of harmonics in BESS/PVDG systems [44,46]. Also listed are the inadequacies of the current controllers of inverters in reducing harmonic contents and the positioning of sensors and locations of BESS and PVDG units in the distribution networks [47–49]. The outer voltage control loop of a two-series control algorithm and the PLL system could be another cause of reference current harmonics. In addition, output current harmonics could emerge from the dead time for switching pulse of the BESS/PVDG inverters [32,43].

2.3. Grid Voltage Harmonics

The BESS/PVDG inverter output current is produced due to the variation between the inverter's AC output voltage and the distribution network voltage. The output current harmonics are generated from the grid voltage when the grid voltage waveform includes harmonic components. The field measurements and research literature revealed that the grid voltages consistently have harmonics in varying degrees at different locations of the network [7,31,42,43]. For example, Figure 2a,b show the measured individual voltage harmonics up to the 31st order for one PVDG inverter at phase B of the grid and the combination of one PVDG and one BESS inverter for harmonics up to order 25 at phase B [31]. Grid voltage harmonics are usually low orders and are very difficult to annihilate by the filters. Numerous methods have been presented to control current harmonics generated from the grid voltage harmonics [50–53]. Du et al. [43] stated that the current harmonics sourced from grid background voltage do not depend on the magnitude of inverter output power. The grid voltage harmonics only reflect the magnitude of output current harmonics [43].



(**a**)



(**b**)

Figure 2. Individual voltage harmonics of phase B at (**a**) PVDG, (**b**) BESS outputs [31].

2.4. Harmonic Standards for Large-Scale BESS/PVDGs

Power quality is a power system requirement stipulated in all the international standards governing the grid connection of BESS/PVDG systems. Table 1 shows the IEEE 1547 and IEC 61727 standards as related to the requirements for current harmonics of the grid-connected BESS/PVDG systems [42,54,55]. The total harmonic distortion (THD) of generated current should not exceed 5% limit.

Table 1. Current harmonics limits by IEEE 1547 and IEC 61727 standards [54].

Harmonics Orders (I_H)	**Corresponding to Fundamental (%)**
A. Odd Harmonics	
3, 5, 7, 9	Less than 4%
11, 13, 15	Less than 2%
17, 19, 21	Less than 1.5%
23, 25, 27, 29, 31, 33	Less than 0.6%
>33	Less than 0.3%
B. Even Harmonics (All)	Less than 25% of various Odd harmonics
Total Harmonic Distortion (THD)	Less than 5%

During the conversion processes, the total harmonics produced by a BESS/PVDG system are in high quantity, despite that the inverters are parallel connected and multileveled [48,54]. This is a big issue when such inverter outputs are delivered into the distribution network. The current magnitude of many high-power inverters together with their harmonic contents can release large quantities of harmonics into a distribution system. This is because the magnitudes of current harmonics is proportional to the active output power of the BESS/PVDG system [7,31]. The loss of power in BESS/PVDG is mostly due to harmonics produced during the BESS/PVDG power conversions. In this sense, the proper location of BESS/PVDG units in the DN will result in network harmonic reduction due to harmonic cancellation effects. Power losses as a result of harmonics is seen as a very challenging issue worldwide due to technical damage and economic losses it causes. The economic losses related to harmonics have been geometrically growing at a high rate in recent years because of the high penetration of large-scale BESS/PVDGs into the distribution system. Consequently, re-evaluating the existing optimization models and algorithms used in the planning allocation of BESS/PVDGs to determine their effectiveness in curtailing the harmonics produced by the BESS/PVDGs is important, while taking cognizance of the huge amount of technical damage and economic losses occasioned by the harmonics.

3. Framework for Optimizing BESS/PVDGs into Distribution Networks

BESS/PVDG optimization is the methodological approach for obtaining optimal locations, sizes and times of BESS and PVDG units and installing them in a distribution network under network operating, investment and BESS/PVDG capacity constraints. The sizing and placement of BESS/PVDG units is a highly constrained, complex, nonlinear, mixed-integer and multi-objective optimization problem whose global optimum solution is very hard to find. The optimization of hybrid BESS/PVDGs involves considering contradicting objective functions such as maximising BESS/PVDG capacity and minimising power quality index; complex decision variables such as DG type, size, location and time; constraints such as network harmonic limits, DG voltage limit and power flow constraint; and the required conditions for modelling the uncertainties, especially the intermittency of the constituent distributed units (inaccurate mathematical model) [4,6,56]. Figure 1 provides the framework for optimizing BESS/PVDG into the distribution networks.

3.1. Optimization Objectives

The BESS/PVDG optimization objective functions can be either a single objective or multi-objective. The common single-objective functions used in the recent research works are minimisation of costs, energy losses, power losses, copper losses, emissions, voltage deviations, total harmonic distortions level (voltage and current); maximisation of benefits, profits, revenue of distribution system, DG capacity, reliability metric; enhancement of voltage profile, voltage stability; etc. The formulation of single-objective optimization problem can be from the perspectives of distribution system operator (DSO), the distribution energy resources developer, etc. [2,4,6,57]. A multi-objective function optimization problem requires the addition or combination of many single objectives that are conflicting and from which a single solution obtained may not be able to solve all the different objectives. The multi-objective function optimization involves simultaneous minimisation or maximisation of decision variables to obtain a single-objective formulation.

3.2. Decision Variables for BESS/PVDG Optimization

The decision variables are the unknown design variables that are determined during BESS/PVDG optimization procedures. The BESS/PVDG decision variables are formed from one or an amalgamation of size, location, number of DG, DG type, generated power of DG, installation year, real power and reactive power of DG or storage device, bus voltage angle and bus voltage magnitude [2,4,6]. The bus voltage angle and magnitude are the variables used for the decisions on the stability and power quality of the network.

3.3. Constraints for BESS/PVDG Optimization

Constraints are used in DG optimization problems to impose restrictions on some decision variables during the optimization of the objective function. Some of the commonly applied constraints in the formulation of DG allocation problems are as grouped [2,4,57].

3.3.1. Investment Constraints

They are constraints enforced on investment variables. Investment constraints can take on continuous, discrete or binary values. For example, the inequality constraints imposed on budget limit, divestment and investment options.

3.3.2. Safety Constraints

These are constraints to guarantee network and people's safety. Examples are the inequality constraints imposed for right of way in the installation of DG units, etc.

3.3.3. Technical Constraints

These are the power generation, network power flow and reliability constraints. These guarantee constant and continuous generation, transmission and distribution of power to the consumers. Some of the technical constraints are:

- The equality constraints for power balance that are imposed on active and reactive power of each network bus.
- The inequality constraints imposed on generations from DG units. e.g., DG penetration limits, discrete sizes of DG units, DG capacity limits, DG unit's constant power factor, maximum number of DGs, etc.
- The inequality constraints imposed on transmission lines and other network equipment/elements, e.g., transmission supply limits, transformer or line-overloading limits, dedicated buses for DG installations, transformer or line capacity limit, etc.
- The inequality constraints imposed on the transmission of power to the consumers, e.g., short-circuit constraints, maximum SAIDI, and radiality constraints.

3.3.4. Network Stability Constraints

Network stability constraints are imposed on the system to ensure power system stability. They are the constraints imposed on voltage drop, bus voltage magnitude, voltage angle, etc. The network stability constraints are formulated based on two network variables—voltage magnitude and voltage angle.

- The voltage magnitude constraints are imposed in the networks to ensure voltage stability. Inappropriate voltage magnitude could lead to voltage instabilities in power systems and cause damage to customers' devices, equipment and apparatuses.

$$\mathrm{V}_{\mathrm{i(min)}} \leq \mathrm{V}_{\mathrm{i}} \leq \mathrm{V}_{\mathrm{i(max)}} \text{ OR } \Delta\mathrm{V}_{\mathrm{i(min)}} \leq \Delta\mathrm{V}_{\mathrm{i}} \leq \Delta\mathrm{V}_{\mathrm{i(max)}};\ \mathrm{i} = 1, 2, \ldots\ \mathrm{n}. \tag{1}$$

The inequality constraint presented in (1) is imposed on all the network buses to enforce voltage stability of the network.

- The phase angle constraints are imposed on the network based on some stability conditions to ensure dynamic stability such as small signal stability of the network. Voltage angle limits are crucial to dynamic stability, as the voltage magnitude is related to voltage stability of the network. Failure to maintain appropriate voltage angle limits can cause enormous dynamic instabilities that can result in total power outage and other serious economic losses. However, almost all the works on distributed generation allocation expansion planning do not utilize voltage angle constraints in the formulation models.

$$\theta_{\min} \leq \mid \angle \mathrm{V}_{\mathrm{i}} - \angle \mathrm{V}_{j} \mid \leq \theta_{\max}; \text{ OR } \theta_{\min} \leq \theta_{\mathrm{i}j} \leq \theta_{\max} \tag{2}$$

This constraint (2) is imposed on all the network buses to enforce some stability criteria.

3.3.5. Power Quality Constraints

These power quality constraints are imposed to ensure the quality of power integrated into the distribution system. Different power quality indices such as total harmonic distortion (THD), total demand distortion (TDD), displacement power factor (DPF), oscillation power factor (OsPF) and transmission efficiency power factor (TEPF) could be used for power quality evaluation. A single power quality index that represents these indices could be formulated to evaluate the power quality of the distribution systems.

- The inequality constraints include voltage rise limits, voltage and current total harmonic distortion (THD) bounds, voltage sag bounds, etc.
- The harmonic constraints can be formulated based on the most important distribution network' constraints such as the voltage magnitude limits and voltage angle constraints.

The voltage magnitude constraints of the system can be reformulated and extended to impose constraints on the voltage harmonics of the distribution system during the integration of BESS/PVDG systems.

$$THD_v = \frac{\sqrt{\sum_{h=2}^{\infty} V_h^2}}{V_1} \tag{3}$$

$$V_{h(\min)} \leq V_h \leq V_{h(\max)}\ ;\ \ h = 1,\ \ldots N \tag{4}$$

Similarly, the phase angle constraints could be formulated considering some parameters and assumptions that relate phase angle to active power (current) and can be extended to distribution networks if current harmonics are expected to be curtailed.

$$THD_I = \frac{\sqrt{\sum_{h=2}^{\infty} I_h^2}}{I_1} \tag{5}$$

$$\theta_{h(\min)} \leq \theta_h \leq \theta_{h(\max)}\ ;\ \ h = 1,\ \ldots N \tag{6}$$

3.4. Modelling the Uncertainty of BESS/PVDGs

Modelling the uncertainties of BESS/PVDG units, including BESS and solar PV units, and the uncertainties of loads are very important to obtaining accurate solutions for a BESS/PVDG optimal allocation problem. The uncertain parameters that can be modelled in the planning of an electric power system for accounting the uncertainties in the distribution system are also presented in Figure 3. However, several previous research works place the uncertainties of these resources into consideration in their formulation models. Some of the uncertainties that are being considered and modelled in BESS/PVDG optimization studies include uncertainties of solar irradiance, wind speed, PV modules, wind and solar DG units, uncertainties of fuel, generated power, electricity market price, uncertainty of BESS and uncertainty of loads [1,4,14].

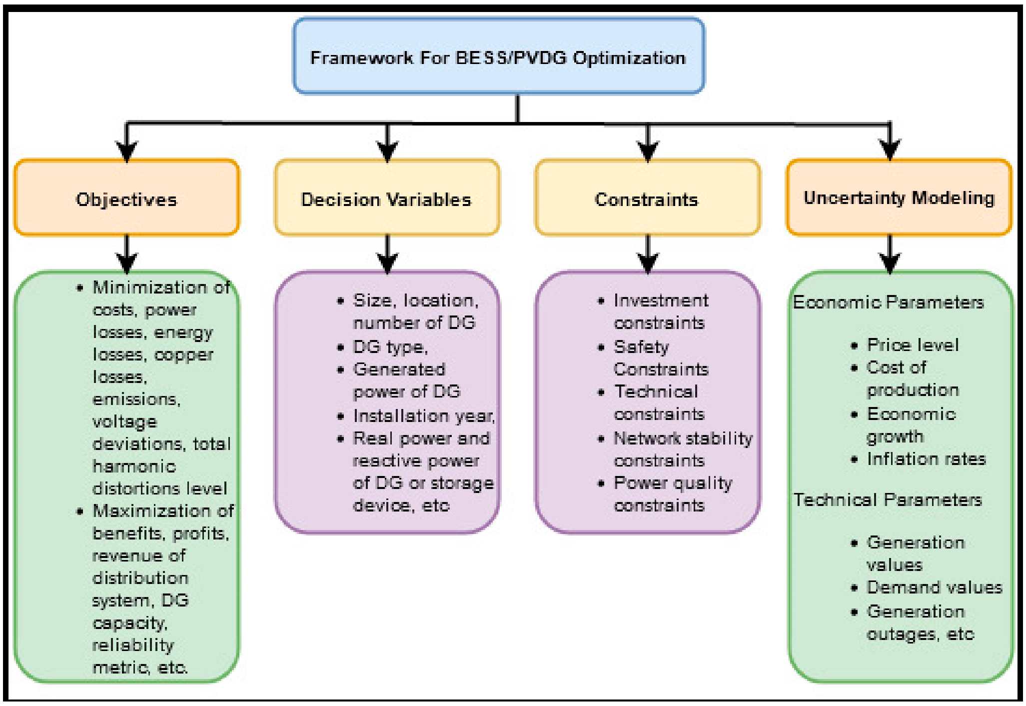


Figure 3. Framework for optimizing BESS/PVDG into distribution networks.

4. Optimization Models and Methods for BESS/PVDGs Allocation

The design and planning of battery energy storage system–photovoltaic distributed generation system is a research area that has continued to generate a lot of interest from many researchers, hence the large number of literature studies on the topic. The planning problem mentioned above concerns the hybrid energy systems that have optimal patterns and whose optimal sizes, placement/location and type of generation components/units can be assigned with minimum costs over the lifetime of the technologies. Therefore, the planning by the minimum net present value (NPV) of cost is called the optimal planning or optimal allocation of all probable hybrid technologies that are in optimal transition [11,24,56,58].

There are several methods for obtaining an optimal planning solution and many real-time, commercially available software applications for energy systems integration. In addition, various researchers have applied different optimal techniques to solve BESS/PVDG allocation problems. Different optimization methods, such as conventional methods, population-based intelligence search methods, some promising heuristic intelligence search approaches and commercial software applications, have been applied by the researchers to optimize hybrid BESS/PV distributed generation systems.

4.1. Conventional Optimization Methods

Conventional optimization methods are analytical and numerical techniques that usually present numerical equations to resolve optimal allocation problems. The methods involve computations, mathematical and theoretical analysis. The accuracy of these methods greatly depends on the efficacy of the model formulated. The advantages of these methods are the ease of implementation and short computation time to obtain convergence for the problem. However, under a complex problem, the accuracy of the solution may not be satisfactory because of the hypotheses used in simplifying the problem. Some of the conventional methods are discussed as [2,57–59].

4.1.1. Sensitivity Analysis Methods

Sensitivity-analysis-based methods use sensitivity indices used to optimally allocate DG units. In these methods, the original nonlinear equations are linearized about their starting operating points to lower the numbers of feasible solutions in the search space. The advantages of sensitivity analysis methods are reduced computation time, which is critical for large practical systems, and good ability to assess the uncertainties of renewable energy resources. Anuradha et al. [60] present a loss-voltage sensitivity index for optimizing the renewable DG size, BESS capacities and power dispatch in distribution networks. The objective is to simultaneously evaluate both minimum effects of network losses and voltage variations for optimizing the DG size [60]. A hybrid of loss sensitivity analysis methods and novel voltage stability index is applied by Murty and Kumar [61] to find optimal sizes and locations of active and reactive power DGs. The objective is to minimise copper losses and enhance network voltage profile. In Saini and Gidwani [62], a comprehensive assessment of battery energy storage system installation and the placement of photovoltaic (PV) units in a radial distribution network is performed utilizing different load models. The objective is to minimise annual energy losses, control overvoltage and reverse power flow problems in a distribution network. Nevertheless, the solutions obtained from the sensitivity analysis methods solely found optimal placements of distributed generators, but the levels of optimality of such solutions are not known [4,58].

4.1.2. Linear Programming

Linear programming (LP) is a method that uses a mathematical model with linear mathematical relationships for optimizing the objective function(s). LP is used in power system optimization problems to obtain optimal sizes of DG units, because it provides precise solutions [2,56,57]. In Altintas et al. [63], the authors proposed a two-objective LP algorithm to incorporate solar and wind renewable DGs as well as BESS into distribution system expansion planning. The objective minimises the total cost of investment and carbon emissions. This algorithm performed a sensitivity analysis test on the effect of investment costs with respect to wind and solar DGs and BESS. Alturki et al. [64] presented an LP method to obtain optimal hosting capacity of a distribution grid with the objective to maximise the PVDG power using some fundamental variables and to minimise total cost using some uncertain criteria. The results revealed that the computation time for the proposed LP algorithm was very small, especially for large-scale problems. However, the network harmonic level and stability were not considered for evaluation in these works.

4.1.3. Mixed-Integer Linear Programming

The mixed-integer linear programming (MILP) method uses a mathematical model with linear objective function and linear constraints in which, at the minimum, one design variable must be an integer. The implementation of MILP is difficult in large-scale problems because it uses too much computation time. In Santos et al. [1], MILP is applied to determine the optimal locations, sizes and timing of smart-grid technologies for minimising the net present value of the total cost and for maximising the renewable DG integration. In Mishra et al. [65], a chance-constrained stochastic MILP algorithm is modelled to determine optimal investment decisions of DGs considering operational uncertainties, while an evolutionary vertical sequencing protocol algorithm is used to further optimize the objective function that minimises the total cost of investment and operation. Santos et al. [66] proposed an improved model aimed at optimizing the system operation in a coordinated way, where distributed renewable energy sources (DRES), energy storage systems (ESS) and distribution network system reconfiguration (DNSR) are considered along with the uncertainty of the resources. The objective function was modelled to incentivize the uptake of DRES by considering the cost of emissions to decarbonize the power system. In Ajeigbe et al. [67,68], the authors applied the MILP algorithm to maximise the optimal allocation of solar, wind and biomass DGs into the distribution system by minimising the NPV of total cost and by confining the small signal stability of the networks to a required level. All the works reviewed here modelled uncertainties of renewable energy resources and evaluated voltage stability of the network but were not able to evaluate the impact of BESS/RERDG powers on the harmonic contents of the networks. Likewise, their results did not report global optimal solutions to BESS/PVDG optimal allocation problems.

LP and MILP suffer from a lack of flexibility. They normally require pre-conditions such as convexity, linearity and continuity of objective functions, which are difficult to meet in practice [2,57].

4.1.4. Nonlinear Programming

Nonlinear programming (NLP) is a mathematical programming method that uses nonlinear objective function and solely continuous variables and constraints. The NLP computation involves the differentials of objective functions and constraints. In solving nonlinear problems, a search path is selected iteratively by defining the starting partial differentials of the problem equation. This approach could be based on first-order or higher-order methods such as the reduced gradient method [69,70] and other search methods [71,72], Newton Raphson method [73] and successive quadratic programming [74,75] which are used for solving DG allocation planning problems.

4.1.5. Mixed-Integer Nonlinear Programming

Mixed-integer nonlinear programming (MINLP) utilizes a mathematical model with nonlinear objective functions and constraints and both continuous and discrete variables. MINLP algorithms have been applied in power systems to determine the optimal sizes and locations of DGs and BESSs. Some of the disadvantages of MINLP are long computation time and a very large number of decision variables [2,56,57]. Salyani et al. [76] applied MINLP in the mathematical modelling for the simultaneous optimal allocation planning of high- and medium-voltage substations, robust medium-voltage feeder routing and renewable DG units. The authors used adaptive GA to find optimal locations and sizes while the uncertainties of renewable DGs, fuel prices, electricity and demand were evaluated. A mixed-integer nonlinear programming-model-based methodology is presented in Valencia et al. [11] for the optimal location, selection, and operation of BESSs and renewable distributed generators (DGs) in medium–low-voltage distribution systems.

4.1.6. Fuzzy Logic

The fuzzy logic (FL) method was developed in 1979 to solve power system problems. The FL method is based on the concept of a classical set, such as the identification of a membership function that is associated with each member as indicated by a binary number 0 and 1 [77]. The membership function dictates the resemblance level of a member in a fuzzy subset. Some of the common membership functions are the triangular, trapezoidal, piecewise-linear and Gaussian functions [2,57,59]. In Injeti and Kumar [78], FL is applied to DG allocation problems, with minimisation of power losses and improvement in voltage profiles as the objective function. Sharma et al. [79] proposed a FL controller in determining the optimal sizes and locations of DGs in order to minimise power losses and to enhance loadability and voltage profiles of distribution networks. However, the results from these works did not report the optimality of their solutions, the evaluation of network stability or harmonic contents.

The works discussed thus far on FL have not considered the impact of DGs and BESS on the oscillatory modes and harmonic contents of the distribution networks. To achieve practical solutions, dynamic networks must be simulated for the evaluation of distribution system stability and harmonic contents.

4.2. Intelligence Search Methods for BESS/PV Distributed Generations

Artificial intelligence (AI) is the application of human intelligence to perform tasks in machines [59]. AI is applied in the intelligence search methods (ISM) used in power systems for optimal sizing and placement of DGs. Intelligence search methods are heuristics algorithms that fasten up the processes of obtaining near-optimal solutions for complex and large DG problems. The advantages of intelligence search methods over other conventional methods is the simplicity of implementation and robustness. However, the accuracy and precision of ISMs are not reliable. They usually take much computation effort [2,56,57,80]. Some of intelligence search methods are presented below.

4.2.1. Genetic Algorithm

Genetic algorithm (GA) is an intelligence search algorithm that was introduced earlier to solve optimization problems. GA is developed from natural selection and genetics principles such as selection, mutation, inheritance and crossover [56,57]. In GA, a set of selection rules is specified to allow a population to achieve a maximum state of fitness. Then, the elements in a population are integrated into chromosomes to enable the potential elements to achieve a better state. The first population of elements evolved through the evolution of generations. The principle of mutation is applied to modify the chosen element to evolve into a new population. The algorithm repeats this procedures until an acceptable solution or the highest number of iterations is attained. [4,6,56]. Genetic algorithms utilize continuous and discrete variables for implementation and work better at obtaining global optimums of various functions. GAs can effectively solve poorly defined and complex problems. GA is the most used optimization method to find optimal locations and sizes of DGs in the literature [22,81,82]. In Liu et al. [22], the authors presented a mixed-integer GA to obtain optimal sizes and locations of hybrid battery energy storage and renewable energy DGs units with objective aiming to minimise system total cost, end-user satisfaction loss caused by demand side management, and tie-line power fluctuation. The methodology in Liu et al. effectively determined the solution of the multi-objective optimization problem compared to others validated with it. However, neither uncertainties of the renewable energy sources nor the voltage variability of the BESS were modelled. In addition, the requirements for the evaluation of network stability and harmonic contents were not included in the proposed methodology. Moreover, genetic algorithms have the disadvantage of evaluating the repeated fitness functions that are time intensive for large and complex problems. The various configurations of GA that are proposed to improve the performance of the GA method in the DG allocation problems are quantum GA (QGA) [83], adaptive genetic algorithm (AGA) [84], etc.

4.2.2. Simulated Annealing

Simulated annealing (SA) uses an iterative procedure for solving combinatory optimization problems. SA employs the process of crystallization at a discrete search space of a physical system [57]. The SA algorithm depends on the cooling criterion and uses initial temperature (T), final temperature (T_{min}) and cooling rate (β) variables. SA algorithms are extensively proposed in the literature to allocate DG units at lower computational time. Simulated annealing algorithms perform effectively in solving reliability-criteria-based optimization problems [2,57]. The advantages of SA algorithms are robustness, simplicity of implementation, and capability to provide feasible solutions to combinatorial problems. Nevertheless, SA algorithms have large computation times without upper limits, terminate at local minimums and lack details on the level of variation between a local minimum and global minimum [56,85]. In Koziel et al. [86], the authors presented a feasibility-preserving SA algorithm to obtain DN reconfiguration with the objective to minimise power loss and improve voltage profile. This study concluded that the proposed algorithm was more efficient than some published population-based intelligence search methods with respect to computational cost and solution repeatability. However, the optimality of the solution was not reported, and the harmonic contents and dynamic stability of the networks were not evaluated in the proposed work.

4.2.3. Particle Swarm Optimization

Particle swarm optimization (PSO) methods are developed based on the social adaptation of flocking bird and schooling fish. In PSO, single intersection of all dimensions produces a particle, and these particles move randomly in a complex search space. The system is then adjusted using a number of solutions that are randomly selected. During each iteration, the particles use their fitness level to assess their positions. Then, the contiguous particles update their previous "best" position to upgrade the final solution [2,57,87]. The advantages of PSO are robustness, simple implementation and running simultaneous computations in less computation time. PSO algorithms use a couple of parameters to modify and converge faster. PSO can also be effectively used to solve DG allocation problems with inaccurate mathematical models. However, the initial design parameter are difficult to define with PSO. During complex DG allocation problems, PSO may converge prematurely and terminate at the local minimum [6,56]. In Prabpal et al. [88], the PSO technique was applied to obtain optimal sizes and locations of multiple BESS and PVDG units with the objective to minimise total cost, minimise the impact of large-scale penetration of BESS, improve voltage profile and increase the stability of the power system. The results showed that PSO and GA methods equally performed better in achieving fewer numbers of iterations and quality of solutions. Shahzad et al. [23], Jamian et al. [89], Rathore et al. [90] and Zeinalzadeh et al. [91] proposed multi-objective PSO methods for determining optimal locations and sizes of BESSs/PVDGs to minimise power losses and improve voltage profiles. However, the uncertainties of the intermittent DGs and BESSs were not modelled, and the impact of their variable output power on the dynamic stabilities and harmonic contents of the distribution networks was not considered. Only the uncertainties related to BESS/PVDG market scenarios were evaluated in Rathore et al. [90].

4.3. Promising Intelligence Search Methods

Promising intelligence search methods are the additional optimization algorithms developed to effectively solve distributed generation optimization problems. Some of these methods are as stated [2,57,59].

4.3.1. Artificial Bee Colony Algorithm

The artificial bee colony (ABC) algorithm was developed from the searching behaviour of a swarm of honeybees. Khasanov et al. [16] proposed an application of hybrid teaching-learning and artificial bee colony (TLABC) technique for determining the optimal allocation of PV-based distributed generation and battery energy storage units in a distribution system with the aim of minimising the total power losses. ABC algorithms are applied in Mohandas et al. [92] and Dixit et al. [93] to find optimal DGs locations and sizes with the objective of minimising power losses and of improving voltage stability of the network. In Abu-Mouti and El-Hawary [94], the authors proposed an algorithm of ABC to adjust the control inputs, iteration number and colony size in the DG allocation optimization. El-Zonkoly and Kefayat et al. [95,96] utilized ABC algorithms to solve distribution expansion planning problems and to obtain optimal reinforcement and commitment scheduling for PVDG allocation. Padma Lalitha et al. [97] presented and compared the ABC and PSO algorithms. The authors observed that the ABC algorithm outperformed PSO, having better solutions and convergence. Notwithstanding, the works discussed here do not provide indices to evaluate harmonic contents and dynamic stabilities of the systems.

4.3.2. Ant Colony Algorithm

The ant colony (AC) algorithm is adapted from ants' social behaviours in searching for the shortest route to obtain food. The AC algorithm process begins with random solutions obtained from the ants' random searches in their movements. Ants share information about their movements by leaving chromosome trails behind during their movements. Consequently, a path with trail density becomes the shorter path. This knowledge is utilized in the optimization search to obtain feasible solutions [57]. The advantages of AC algorithms are the ability to discover good solutions and guarantee convergence and the ability to search among a population simultaneously and adapt to changes such as new distances. However, AC optimization algorithms are weak in changing probability distribution, uncertainty of convergence time, sequences of random decisions and theoretical analysis, since they are highly experimental researches. These algorithms are variously used in the literature for optimal allocation of DGs [6,56]. In Gomez et al. [98], Vlachogiannis et al. [99], Wang and Singh [100] and Amohadi and Fotuhi-Firuzabad [101], the variant of AC and ant colony system (ACS) algorithms were presented. They found optimal sizes of DGs, locations of DGs and re-closers in the radial DNs with an objective to use the composite reliability index. Transient stability and reliability of the distribution systems were evaluated to validate the proposed methods. ACS algorithms were observed to be more satisfactory in many engineering applications. However, these works did not include the installation of renewable DGs and could not access the impacts of integrating BESS/PV-distributed generations on the harmonic distortion and oscillation of the networks.

4.3.3. Artificial Immune System Algorithm

The artificial immune system (AIS) algorithm is adapted from immunology, the importance of the immune system and their values in the natural world [102]. The immune system is an indispensable defence against self-approach to protect human health from pathogens such as viruses and microbes. The procedure differentiates between self-cells and non-self-cells. Thereafter, the immune system effects immune actions to destroy the non-self-cells [103–105]. To apply the AIS optimization process in solving DG allocation problems, the instructions in the search area (objective functions, design variables, constraints, etc.) are encrypted in an antigen population of an AIS algorithm. AIS algorithms are proposed in Aghaebrahimi et al. [106] and Hatata et al. [107] to find the optimal locations and sizes of the DGs, with the objective to minimise the power losses of the DN considering bus voltage limits and line current. Souza et al. [108] proposed an AIS algorithm in expansion planning to allocate DG units into distribution network considering the uncertainty of load demands.

4.4. Probable Hybrid Intelligence Search Methods

Hybrid optimization methods are a useful combination or collaboration of more than one different intelligence search method. These approaches extract the benefits of the component methods to obtain an optimum solution for a specific planning problem. The allocation expansion planning of BESS/PVDGs problems is multi-objective in nature. Hence, applying a hybrid method in their investigation begets an excellent planning objective and a suitable alternative algorithm to solve the problems that involve better understanding of the methods.

A summary of the various optimization techniques that are developed and applied by the researchers for BESS/PVDGs allocation is presented in Table 2.

Table 2. Summary of optimization methods.

Optimization Method	Optimized Factor	Comment
Conventional Method • Sensitivity Analysis [60–62] • Linear Programming (LP) [63,64] • Mixed Integer Linear Programming [65–68] • Nonlinear Programming (NLP) [69–75] • Mixed-Integer Nonlinear Programming (MINLP) [76] • Fuzzy Logic [77–79]	Hybrid renewable energy sources (solar, wind) and battery energy storage, and cost	Using numerical equations that can be applied to optimization problems due to their capability to provide accurate mathematical model formulation
Intelligence Search • Genetic Algorithm [81–84] • Simulated Annealing [85,86] • Particle Swamp [87–91] • Artificial Bee Colony [92–97] • Artificial Immune System [102–108] • Ant Colony [98–101]	Hybrid renewable energy sources (solar, wind) and battery energy storage, and cost	Using the exhibition of intelligence in machines to determine optimal locations and sizes of hybrid DGs in power system
Deterministic Approaches [59–63]	Standalone renewable energy sources (solar, wind) with battery energy storage, and cost	Using mathematical equations for determining particular values when fixed factors are set

Table 2. *Cont.*

Optimization Method	Optimized Factor	Comment
Probabilistic Approaches [63–67,74,75]	• Efficiency of hybrid renewable energy systems, and cost • Uncertain parameters in power system	Using statistical data gathering methods for finding optimized factors
Software Based Methods [109–116] • HOMER • HYBRIDS, etc.	Hybrid solar/wind and or diesel generators with battery energy storage	Using software applications that uses input file with all necessary data

4.5. Commercial Software Applications for Allocation of (BESS/PV) Hybrid DG Systems

Several software applications have been developed and applied for the sizing of hybrid renewable energy systems (HRESs) such as HOMER [109–111], HYBRIDS [112], HYBRID 2 [113], RET Screen [114], TRNSYS [115] and IHOA [116].

Comparatively, HOMER has a significant application in optimal sizing of HRESs because of its capacity to quickly obtain optimal sizes of energy systems. In addition, it is useful in investigating sensitivity analyses of some uncertainty parameters and changing factors related to the HRESs. However, the mentioned software tools are incapacitated to investigate major network system issues related to the integration of distributed HRESs (DHRESs) such as harmonics and small signal and transient stabilities. A list of commercially available software for the planning of HRES is presented in Table 3.

Table 3. Software applications for optimizing BESS/PVDGs.

Name of Software	Optimization Input	Optimized Output
HOMER	• Load command • Resource input • Cost details (capital, O&M, replacement costs • System control	• Optimize unit size(s) • NPV and energy cost
HYBRIDS	• Wind turbine size(s) and type • Solar size(s) • Type and number of battery storage	• NPV and energy cost • Amount of green-house gases
HYBRID 2	• Resources input • Load demand • Cost details (O&M, investment, components costs)	• Optimize unit size(s) • NPV and energy cost • Proportion of green-house gases released. • System payback time
RET SCREEN	• Load command • Solar size(s) • Climate data input • Invention and hydrology data input	• NPV and energy costs • Economic capability • Production rate • Risk analysis • Energy used and saved
IHOGA	• Load command • Resources data input • Components and economic factors	• Improve multi-objective optimization • Cost of energy • Life cycle release
TRYSYS	• Climate data • Ingrained models	• Dynamic simulation of renewable energy resources

5. Results and Discussion

The increasing needs for energy and the resultant environmental issues arising from fossil energy utilization have encouraged the extensive study of renewable energy technologies in place of traditional fossil fuels. Precisely, hybrid distributed generations, which have been described as a collaboration of renewable energies and support systems, are a significant alternative to confront the concerns over sustainability of energy demands and environmental safety. The planning and optimization of hybrid distributed power systems can meet the essential requirements of a geographical location in terms of availability of potential energy resources, area topography and various kinds of energy demands. Consequently, the optimal allocation of renewable energy sources and storage systems relating to environmentally friendly hybrid distributed systems considerably improves the technical and economic aspects of the power supply system. The addition of storage technologies in the allocation of distributed generations can smoothen output power and reduce REHDG intermittent effects in the network. Including storage devices in the DGs allocation problems provides supporting services to the optimal solutions by eliminating the effects of intermittency in the renewable sources power output. Several allocation methodologies have been proposed to determine the best hybrid renewable energy system with respect to the economy and technology. Determining the optimal allocation of hybrid battery storage and PV-distributed generation systems and other hybrid renewable energy systems is important to increase the technical and economic efficiency of the power distribution system and to encourage the extensive use of environmentally friendly resources.

Various allocation methodologies presented in the recent literature with different optimization algorithms are reviewed here. The GA, PSO, SA and AIS are some of the feasible artificial intelligence algorithms used to investigate the planning and optimization of DG allocation problems. The most important benefit of GAs are the ordered capability to find the global optimal and the ease of achieving a local minimum when used in hybrid system allocation. Another advantage that makes GA suitable for allocation planning studies is code-ability because it is not accessible in other methods such as PSO. For instance, when at most three parameters are to be coded such as in a wind/PV/BESS system, both GA and PSO can perform effectively. However, when more than three elements are involved, only the GA method would be more capable of obtaining optimal solutions. Some other times, PSO has some advantages over GA, although both are very effective in utilizing the same repeatable search approach. Moreover, employing SA in hybrid distributed systems is not as common as GA and PSO methods, but presently, SA is generating more research interest in some approved areas of application. The ACS algorithms have been presented to reduce power losses and to improve power system factors of a radial distributed system. Similar to GA, the AIS optimization algorithm has "collection" and "transformation" operatives which improve the probability of the algorithm to find the global optimum point.

AIS is bound to have a high application in sizing studies because it is similar to GA and can be effective in finding the global optimum in difficult problems. However, GA has greater application than AIS, especially in addressing a large number of parameters. In addition, conventional methods such as LP, MILP and NLP are still being applied in existing studies to detail the features of any physical system into a mathematical model formulation. Often, hybrid optimization methods are applied by combining two or more methods to take beneficial advantage of them in terms of their convergence time during the optimization process. Hybrid methods are characterized due to their dynamic flexibility during the allocation process. Hence, they are the most applied allocation methods.

The intermittent nature of photovoltaic and wind output power and the high voltage rise and fall from BESS cause harmonic distortions which have a negative impact on the power quality, reliability and stability of the distribution networks. The majority of the current works do not include the uncertainties of the renewable and battery storage power sources in their formulation models. They did not combine all the associated investment, technical, safety, DG capacity, network stability, power quality and reliability constraints in the formulation models for the DG allocation problems. In most of these works, the minimum harmonic level and dynamic stability of the network are not constrained but are only assumed, while the constraints for the right of way are neglected for the required buses. All these necessary and associated constraints need to be incorporated to obtain a practical solution from the REHDG allocation models. In essence, future research studies should give adequate consideration to modelling of the impacts of renewable energy intermittencies and the resulting variable output power to culminate in more feasible solutions to BESS/PVDG optimization problems.

In addition, the operations of hybrid DG systems are dynamic. Hence, the planning and design of optimal sizes and placement of RERDGs should be optimized on dynamic networks but not on static ones, as they are mostly performed in the existing planning models. The dynamical issues such as harmonic and system instabilities are very visible while using dynamic networks, since the real power networks are dynamic networks whose load profile periods are estimated hourly during a dynamic planning horizon. Future research needs to focus on the use of dynamic networks to entirely incorporate the intrinsic characteristics of the distribution network such as the harmonic components and dynamic stability of the network.

Moreover, the sizes and locations of battery energy storage, photovoltaic and wind DG units in the distribution network (DN) affect the network harmonic contents by having either positive or negative impacts on the magnitude of the current and voltage harmonics of the networks.

6. Conclusions

This study presents a review of prior research on the optimization methodologies for designing and planning hybrid renewable energy resource distributed generation such as hybrid battery energy storage–photovoltaic DG and other hybrid distributed systems. This paper reviewed more than one hundred papers published by renowned referenced journals on battery energy storage systems and renewable energy resources as well as on robust and efficient optimization methods for solving hybrid DG allocation planning problems. Optimization studies, in the last decade, on DG allocation planning using conventional and intelligence search methods have been analysed, and hybrid optimization algorithms have been presented.

Intelligence search methods have been mostly used in the last decade due to their capacity for shorter computation times, and because they provide better accuracy and have better convergence than the conventional methods. In conclusion, at the beginning, this study investigated a number of research works that have applied optimization methods to solve renewable energy DG allocation problems, including solar, wind and battery energy systems. Many research works use intelligence search methods, most especially GA, PSO and AIS, to solve these allocation problems. Notwithstanding, conventional methods, especially LP and MILP and different configurations of NLP methods are still being used in current studies. In the case of curtailing harmonic distortions of the DNs, which indicate the strength of this study, an optimal planning model is yet to be developed for optimal sizing, placement and timing of renewable DGs and battery energy storage systems. Although, in most cases, the optimal sizing and placement of BESS/REDGs may have attained a minimum cost, the requirements for minimum harmonic levels are yet to be achieved. These requirements are merely presumed in the existing works. Further research is required in this regard to improve the current expansion planning model to obtain optimal allocation of BESS and renewable energy DGs and to constrain the decision variables related to harmonic distortions to a required level. A more comprehensive expansion planning model together with an efficient intelligence search algorithm that has that capability to obtain a global optimum solution is an important approach towards solving optimal BESS/PVDG allocation problems and towards reducing harmonic components of distribution systems during the integration of hybrid battery energy storage systems and photovoltaic DGs.

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